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Network Proximity and Business Practices in African Manufacturing*

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Abstract

We document empirical patterns of correlation in the adoption of technological innovation and contractual practices among manufacturing firms in Ethiopia and Sudan. The analysis is based on network data indicating whether any two firms in our sample do business with each other, whether they buy inputs from a common supplier, and whether they sell output to a common client. We only find limited support for the commonly held idea that firms that are more proximate in a network sense are more likely to adopt similar practices. For certain practices, adoption decisions appear instead to be local strategic substitutes: if one firms in a given location is using a certain practice, others nearby are less likely to do so. These results appear out of tune with the policy discussion of how the economic performance of African's manufacturing sector can be improved.

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1. Introduction

Technological upgrading and institutional innovation are critical to improve productivity and growth. This is particularly true in Africa where productivity has remained low. This begs the question of why productivity-enhancing innovations have not diffused equally to different countries or regions (Parente and Prescott 1994).

This question has attracted a lot of attention in economics. One strand of literature has focused on the transfer of innovations across countries. Researchers have investigated whether firms learn from exporting, often arguing that exporting facilitates technology transfer because it puts firms in contact with more advanced firms in other countries. It is suspected that these contacts provide information about existing technological and institutional innovations while international competition provides the incentive to adopt them in order to remain competitive (Tybout 2000, Kray, Soloaga and Tybout 2002). Studies that investigate whether foreign direct investment raises the productivity of domestic firms typically follow a similar reasoning. The implicit assumption is that domestic firms observe the way foreign firms operate, and learn from it. In a similar vein, Casella and Rauch (2002) and Rauch and Casella (2003) examine whether entrepreneurs with better business contacts abroad behave differently.

Another strand of literature has examined the diffusion of innovations within countries and regions. Here too a shared underlying assumption of much of this literature is that, by interacting, firms learn from each other about technological and institutional innovations that raise productivity. While there is a body of rigorous research on technology diffusion among farmers (Griliches and Lichtenberger 1984, Young and Burke 2001), much of the existing literature on manufacturing firms remains fairly descriptive, relying principally on case studies (Sutton 1998, Sonobe and Otsuka 2011). While much can be learned from such studies, the danger is that too much weight is given to rare or unusual events. For instance, it has been argued that, by diffusing innovations, the sending by Daewoo of Bangladeshi workers to Korea for training played a key role in the emergence of a successful garment industry in Dacca (Doshi 2011). The problem with this kind of evidence is that it leaves out many situations in which workers were sent abroad for training but did not trigger the emergence of a new industry in their home country. Whatever rigorous evidence there is on the diffusion of innovations across firms pertains to developed economies. Helmers (2010), for instance, documents technology diffusion across firms in UK business incubators. There is shortage of rigorous statistical evidence on the diffusion of innovations across firms in developing countries.

The purpose of this paper is to offer statistical evidence about the possible diffusion of innovations among firms. Our aim is modest: we examine whether innovative business practices are correlated more between firms when they are close in a network or market sense. We are fully aware that finding evidence of correlation does not prove diffusion: business practices could be correlated across firms because of contextual effects, such as the influence of a common, and possibly unobserved, factor. But finding no evidence of correlation suggests that business practices do not diffuse as much or as easily as is often believed.

There are two important caveats to this interpretation. The first is that diffusion be slow enough to be observed in cross-section data: if new practices diffuse very fast and all firms belong to a single connected network, the probability that we would observe an economy in the middle of a diffusion process is small. The second caveat is that strategic complementarities in the adoption of new practices must dominate possible strategic substitution effects between firms. Put differently, it must be true that adoption by some raise the incentive for other, proximate firms to adopt as well. For the kind of business practices that we study, these two caveats are a priori likely to be satisfied.

We also investigate which measure of proximity best accounts for correlation in practices.

This can suggest possible avenues for future enquiry. For instance, if we find that firms that buy and sell from each other share certain practices, this suggests that direct contact between firms may be important for diffusion. If in contrast we find more correlation in innovative practices among firms that sell to the same clients or to clients in the same region, this suggests that competition for customers may provide a strong impetus for firms to imitate each other.

We use cross-section survey data collected in Ethiopia and Sudan. These two countries are good candidates to study diffusion. First, they cover a very large area and both have a small manufacturing sector, making interaction between firms less frequent and diffusion more problematic. Given this, it is more likely that we observe differences in business practices across firms because diffusion is not complete. Secondly, the average technological level of the surveyed firms is low, thus leaving much room for even simple innovations to boost productivity. Finally, both countries have little economic contact with the rest of the world. In the case of Ethiopia, this is partly due to the fact that the country is landlocked and mountainous, partly to a history of relative economic isolation. In the case of Sudan, the relative lack of economic interaction with the rest of the world results partly from years of civil warfare, partly from the size of the country relative to its population, and partly to international sanctions. Relative isolation means that there is more room for diffusion to take place among domestic firms rather than directly from foreign to individual domestic firms. Given this, domestic networks should matter more, facilitating inference.

We find some evidence of correlation in business practices. But the evidence is less convincing than one would expect if diffusion effects were strong. We also find evidence that, along some dimensions – principally geographical distance, firms are more similar to distant firms that to those located nearby. This suggests that some adoption decisions are local strategic substitutes: if some firms adopt a certain practice, this may reduce the incentive for others to do likewise.

This is partly confirmed by noting that the practices for which we find evidence of strategic substitutes – R&D, vocational training to workers – are those most vulnerable to free riding by other firms.

What should we make of these results? First we again note that correlation in practices does not imply diffusion; there may be unobserved contextual effects. Secondly, the evidence presented here does not imply that the diffusion of innovation between firms can never be important or even critical. We only say that diffusion between firms should not be taken for granted: many of the firms in our sample follow antiquated business practices even when some neighboring firms do not. Thirdly, it is possible that we looked for diffusion in the wrong place, i.e., among existing firms. Perhaps the diffusion of innovations takes place not so much because existing firms learn to imitate each other, but rather because new firms emerge that adopt innovative practices. This interpretation is consistent with findings reported in the exporting literature, e.g., there is limited evidence that incumbent firms learn from exporting, but ample evidence that firms that begin exporting are more productive than average, even when they are new entrants (Fafchamps, El Hamine and Zeufack 2008).

The paper is organized as follows. Section 2 discusses the conceptual framework and some key methodological issues. Section 3 provides information about the data. Econometric results are presented in Section 4 while Section 5 concludes.

2. Conceptual Framework

2.1. Diffusion

In recent years, theoretical models of diffusion have made much progress thanks to the work of physicists and epidemiologists working on the spread of diseases. The novelty is to model diffusion as operating on a network, where nodes represent individuals and a link between two nodes exists if one node can communicate the disease to the other. We refer to Jackson (2009) and Vega-Redondo (2006) for excellent summaries of this literature. What this work has shown is that, in the long run, diseases tend to diffuse to all connected nodes. Hence nodes that are connected, that is, that are in the same component will either all be infected or all be uninfected. This means that, in the steady state, infection is correlated among nodes in the same component but, within components, network distance does not matter.

In the short run, however, this is not the case: even within components infection rates are more similar between nodes that are close to each other in the sense of having a shorter network distance between them. This is because the disease spreads along the network so that, if a node i is infected, then it is more likely to have – directly or indirectly – passed or received the disease to a node j that is close than to a node k that is more distant in the network. This simple observation forms the basis of our testing strategy.

The circulation of information among economic agents can be modeled in a similar fashion. Let i and j be two agents in a population of size N and let a link g_{ij} exist between them if i and j share information. Assume that one agent in the population, say k, learns a new piece of information and shares this information with its network neighbors who, in turn, share it with their own neighbors, etc. Let $y_i = 1$ if agent/node i knows this information and $y_i = 0$ otherwise. By the same reasoning as in the case of diseases, the new information progressively diffuses across all connected nodes until $y_i = 1$ for all nodes directly or indirectly connected to k. Before the information reaches all nodes in the component, however, we expect that y_i and y_j to be more similar (either both 0 or both 1) if i and j are close in the network.[1]

Now consider that the new information is about the usefulness of an innovation. More precisely, assume that node k discovers (or learns about) a new profitable practice. If adoption

[1]The model also predicts that $\Pr(y_i = 1)$ is an increasing function of proximity to node k. Since in our data we do not know the source of the information, we cannot test this prediction so we ignore it here.

of the new practice is individually optimal for each agent in the diffusion network, we expect adoption of the new practice to diffuse in the same way information about its profitability diffuses, and hence, before the new practice diffuses to all connected nodes, we expect adoption to be more similar across proximate nodes than across distant nodes.

2.2. Strategic complements

Whether or not adoption is individual rational may depend on the number or proportion of adopters in one's immediate neighborhood. In particular, it is common for innovations to be strategic complements between firms: the incentive to adopt a new technology or business practice often increases with adoption by others nearby. This is especially true for contractual practices.

To illustrate this, consider invoicing in a world where cash-and-carry is the norm. Relative to cash-and-carry, it is easier for firms to conduct business if suppliers invoice clients at the end of the month for the deliveries made during that month. This is because invoicing decreases transactions costs and reduces the need to carry and transport large cash balances (Fafchamps and Minten 2001, Fafchamps 2004). But suppose a single supplier introduces invoicing while others continue to insist on payment upon delivery. Negative shock to clients' businesses will trigger defaults or delayed payment towards the invoicing supplier but not towards others. This means that the invoicing supplier bears all the risk of non-payment. If this risk is large enough, no supplier will want to switch to invoicing unless other suppliers do the same.

In this case, decentralized diffusion is still possible but is more difficult. To illustrate this point, imagine that each client has two suppliers and each supplier has two clients, and that suppliers and clients are staggered as in Figure 1. Suppliers can either sell with payment upon delivery or using invoicing, but they must treat all their clients the same. Further assume that a supplier is unwilling to switch to invoicing if *none* of the other suppliers of its two clients offers invoicing, but is willing to switch if at least *one* the other suppliers offers invoicing. In this case, it is possible for invoicing to spread. This is illustrated in Figure 1. Suppose that supplier S_1 adopts invoicing at time t_0. It then becomes optimal for supplier S_2 to adopt invoicing in the next period t_1. This in turn induces supplier S_3 to adopt invoicing at time t_2, and so on. What the Figure illustrates is that, until all suppliers have adopted the new practice, adoption behavior is more similar between suppliers who share the same clients – or among clients who share the same suppliers since, in this case, clients enjoy the benefits of invoicing from their suppliers.

2.3. Strategic substitutes

It is also possible for adoption decisions to be strategic substitutes. Since our purpose is empirical, it is beyond the scope of this paper to offer a general model of strategic substitutes. We propose instead to illustrate our reasoning with a simple example. Imagine that two supermarkets must locate on a circle. Customers shop at their nearest supermarket to minimize transactions costs. In the two supermarkets locate as far away from each other as possible, e.g., North and South, and attract half of the customers. The reason is that territorial overlap generates more competition and reduces profits. Now introduce small stores that do not directly compete with the supermarket but benefit from an agglomeration externality – e.g., a shopping mall. In equilibrium we expect to observe a combination of supermarket and small stores in North and South.

To see how this model generates some intuition for innovation adoption, think of supermarkets as modern firms. They compete with each other for customers and, though some Schumpeterian process, copy each other's innovations. Consequently their practices will be similar even though they are located far from each other geographically and do not share customers. In contrast, think of the small shops as firms serving a localized niche market. Since they are not in direct competition with the modern firm, there is less Schumpeterian pressure for them to adopt the same practices. Hence they can afford to remain fairly traditional in the way they operate, free riding on the local externalities generated by the modern firm. In this world, we should observe that firms' business practices are, on average, more similar with those of distant firms than with those of neighboring firms.

For instance, one firm may set up an R&D department to facilitate the adaptation of innovations from elsewhere to its products and production process. This in turn may reduce the incentive of other nearby firms to develop their own R&D department because they can free ride on the technology adaptation and product development of the R&D firm. Vocational training is another possible example: if one firm upgrades the skills of its workers, other nearby firms may choose instead to hire trained workers away instead of offering their own training.

Yet another example is reputational punishment. Suppose that one firm circulates information about good and bad clients to other firms in the vicinity, and refuses to trade with bad clients. Nearby firms benefit from this information because it helps screen out bad clients. They may also benefit from the punishment imposed on bad clients if this punishment forces them out of business. They enjoy these benefits even if they do not, themselves, share information on good and bad clients. They may even find that punished bad clients are now willing to accept less attractive transaction terms from them (Fafchamps 2010).

Much of the literature on the adoption of new institutions and technologies has explicitly or implicitly assumed that innovations diffuse, which implies that adoption decisions are strategic complements. Yet we have presented some examples, not altogether unreasonable, in which adoption decisions are strategic substitutes. It is therefore fair to say that, on a priori grounds, we do not know a priori whether all adoption decisions are strategic complements or substitutes and, if they differ, which are more likely to fall into one category or the other.

2.4. Testing strategy

Our testing strategy is inspired of the above reasoning. Each enterprise is a node. We observe whether an enterprise i has adopted a practice y_i. Vector $\mathbf{g}_{ij}$ represents network links between two enterprises i and j while d_{ij} represents the geographical distance between them. We want to test whether two enterprises i and j are more likely to have a similar practice if they are close in a network and geographical sense, that is, if $g_{ij} = 1$ for some element of $\mathbf{g}_{ij}$ or if d_{ij} is small. We estimate a model of the form:

$$|y_i - y_j| = \mathbf{g}_{ij}\boldsymbol{\theta} + \omega d_{ij} + \mathbf{x}_{ij}\boldsymbol{\gamma} + u_{ij} \tag{2.1}$$

where $\mathbf{x}_{ij}$ is a set of control variables included to reduce omitted variable bias and u_{ij} is an error term and the greek letters are coefficients to be estimated. As explained in Fafchamps and Gubert (2007), equation (2.1) works irrespective of whether y_i is a continuous or dichotomous variable. A negative $\boldsymbol{\theta}$ in (2.1) means that y is more similar when firms i and j have a link g_{ij}. For geographical distance d_{ij} the interpretation of the sign of ω is reversed. Conversely a positive θ or negative ω means that linked or nearby firms are more dissimilar. If slow diffusion takes place along network g_{ij} we expect adoption decisions to be more similar if firms are linked, i.e., if $g_{ij} = 1$, and hence we expect $\theta < 0$. If diffusion is faster within a region than across regions, we expect $\omega > 0$.

If diffusion is very rapid, we do not expect to observe any difference in behavior between firms in the same component. If all firms belong to the same component then (2.1) reveals nothing about the diffusion process. In contrast, if diffusion is rapid but firms are in different components, then adoption decisions should be more similar among firms in the same component. Since we do not observe the entire relevant network, we do not have the information required to identify components. But we can hazard some guesses. Given the size of the two countries we study, arguably the most serious obstacle to diffusion is geographical distance which, in both countries, is potentially compounded by ethnic differentiation. If geographical distance divides firms into unconnected sub-graphs, then firms located near each other should be more similar and we should observe a strong positive ω. Similarly, if diffusion does take place across sectors, firms in different sectors should be more similar to each other than those in different sectors.

While there is a clear theoretical distinction between rapid diffusion within distinct components and slow diffusion within a connected network, for our purpose this distinction is empirically irrelevant: if all firms belong to a single connected network but diffusion is more rapid within a region or sector, then our methodology will pick this up, and that is what matters. What we are ultimately interested in is to identify along which dimensions – geographical, sectoral, network-based – diffusion is most likely to take place.

Since by construction, $|y_i - y_j| = |y_j - y_i|$, it follows that x_{ij} regressors must be formulated such that:

$$\mathbf{g}_{ij}\boldsymbol{\theta} + \mathbf{x}_{ij}\boldsymbol{\gamma} = \mathbf{g}_{ji}\boldsymbol{\theta} + \mathbf{x}_{ji}\boldsymbol{\gamma}$$

This implies that network and geographical proximity regressors in $\mathbf{g}_{ij}$ must be undirectional, i.e., such that $g_{ij} = g_{ji}$ for each g in $\mathbf{g}$. Similarly we need $\mathbf{x}_{ji} = \mathbf{x}_{ij}$. The purpose of including $\mathbf{x}_{ij}$ is to control for similarity in characteristics between firms that may be correlated with proximity $\mathbf{g}_{ij}$, and hence to reduce omitted variable bias. Let z_i denote one such characteristic. To ensure that $\mathbf{x}_{ji} = \mathbf{x}_{ij}$, we follow Fafchamps and Gubert (2007) and create regressors of the form $|z_i - z_j|$. The estimated model is:

$$|y_i - y_j| = \mathbf{g}_{ij}\boldsymbol{\theta} + |\mathbf{z_i} - \mathbf{z_j}|\boldsymbol{\gamma} + u_{ij} \tag{2.2}$$

A positive and significant γ means that firms that share a similar z tend to have a more similar y.

Equation (2.2) is a dyadic regression model. The dependent and independent variables are defined for every pair of firms i, j in the data, which implies there will be $n \times (n-1)$ observations underlying the regression (n denoting the number of firms). Dyadic observations are typically not independent since residual u_{ij} is likely to be correlated with u_{ik}. This complicates the computation of standard errors. In particular, robust standard errors must correct for cross-observation correlation in the error terms involving the same enterprises. To obtain consistent standard errors, we use bootstrapping. Let $\widehat{\boldsymbol{\theta}}$ and $\widehat{\boldsymbol{\gamma}}$ denote the parameter estimates obtained from estimating (2.2). Bootstrapping is implemented as follows: (i) we draw a random sample s of n firms by drawing from the firm-level dataset with replacement; (ii) for this simulated sample of n firms we construct the corresponding $n(n-1)$ dependent variables $|y_i - y_j|_s$, links $\mathbf{g}_{ij}^s$ and controls $\mathbf{x}_{ij}^s$; (iii) we estimate equation (2.2) for this sample and store the parameter estimates $\widehat{\boldsymbol{\theta}}_s$ and $\widehat{\boldsymbol{\gamma}}_s$; (iv) after repeating the process (i)-(iii) J times, we use the standard deviations of $\widehat{\boldsymbol{\theta}}_s$ and $\widehat{\boldsymbol{\gamma}}_s$ as estimates of the standard errors of $\widehat{\boldsymbol{\theta}}$ and $\widehat{\boldsymbol{\gamma}}$.

As emphasized in the introduction, a significantly positive θ does not by itself imply network diffusion: firms i and j may have correlated technology and contractual practices for reasons other than network or geographical proximity, e.g., because they are subjected to similar contextual effects not adequately controlled by $\mathbf{x}_{ij}$. If unobserved contextual effects are correlated with proximity g_{ij}, they would bias θ above 0. Hence if we find a significantly positive θ, it may be due to diffusion or to unobserved contextual effects. However, if we find that θ is negative or not significantly different from 0, it means that the net effect of diffusion and contextual effects is likely to be negative or zero. The only possible exception is if diffusion is rapid and all firms belong to a single connected network, in which case our identification strategy will fail. But if diffusion is rapid among all firms, then we should observe little variation in practices among firms which, as we will see, is not what we find. If we believe, as is reasonable, that unobserved contextual effects could only generate positive correlation in technology and business practices, then a non-significant θ indicates that network diffusion is 0 while a negative θ suggests the presence of strategic substitution effects in adoption decisions.

3. Data

To implement our testing strategy we use detailed firm-level data collected under the leadership of the World Bank in Ethiopia and Sudan. Virtually the same questionnaire and sampling strategies were used in the two countries. One of the authors was involved in the partial design of the questionnaire.

For Ethiopia, the data on urban Ethiopian manufacturing firms were collected as part of the Ethiopia Investment Climate Survey, fielded by the Ethiopian Development Research Institute (EDRI) in mid-2006. The survey covered 14 major cities located in seven regions of Ethiopia. Approximately half of the observations come from Addis Ababa. As shown on the map in Figure 2, the survey has wide geographical coverage, with long distances between some of the firms in the sample. The average distance between any two firms is 282 kilometers. The longest distance recorded in these data is 876 kilometers, which is the distance between Dilla in the South and Adrigat in the North. The national manufacturing census provided the sampling frame for the survey. The survey concentrates on firms with at least five permanent employees, and covers four sectors: furniture, wood and metal; food and beverages; leather and leather products; and textile and garment. Three hundred and sixty manufacturing firms were surveyed. See Mengistae and Honorati (2009) for more details on the survey methodology.

For Sudan, we use the data on urban Sudanese manufacturing firms collected as part of the

Investment Climate Survey launched in November 2007 and conducted by H&H Consultancy, a Sudanese management consulting firm with expertise in conducting complex surveys. The survey covered 432 manufacturing firms, most of them private, in 8 states. The capital city of Khartoum accounts for 50% of the sample. The survey concentrates on firms with permanent employees, and does not cover microenterprises. The manufacturing survey is very diverse in terms of sectors – no sector represents more than 20% of the sample, with the largest sectors being food and beverages (18%) and fabricated metal products (16%). See H&H (2008) for more details on the survey methodology. After deleting observations with too many missing values, we obtain a sample of 304 firms for Ethiopia and 401 firms for Sudan.

Summary statistics are shown in Table 1. Key firm characteristics are presented first. These are variables thought to influence – or be associated with – innovation adoption. They constitute our control vector. More experienced firms and those with a better quality management should be more adept at recognizing the value of new technologies and practices. Female ownership is included because, in the study of de Mel, McKenzie and Woodruff (2009), female-headed businesses have been shown to be less growth oriented (see also Fafchamps 2003). We also include firm size, as proxied by the (log of) total firm employment. The average log employment is 3.37 in Ethiopia, which corresponds to 29 employees. The largest firm in the sample employs more than 3,000 employees. For Sudan, the average log size is 2.91 which corresponds to 18 employees.

Next we report information on firm technology and business practices. We focus on variables that show some variation across firms in the two samples we have. Practices that vary little across firms are ignored since they offer little or no information about diffusion. For instance, most if not all sampled firms in the two countries have a bank account but virtually none has an ISO certification.[2] From the point of view of entrepreneurs in the two study countries, both practices are innovations but one has been fully adopted by the surveyed firms[3] while for the latter adoption has barely begun.

In the conceptual section we built on Jackson (2009) to argue that the stronger strategic complementarities are, the harder it is for decentralized diffusion to take place in loosely connected networks. We thus begin by reporting variables for which strategic complementarities across firms are a priori thought to be less strong, such as the adoption of technological innovations; we end with variables for which strategic complementarities are likely to be largest, such as reputation mechanisms.

Within each category, adoption by a given firm may be correlated across individual practices, either positively or negatively (e.g., if some practices are partial substitutes for each other). In this case, examining each practice separately is likely to yield inefficient inference. To guard against this possibility, we summarized the available information within each category using factor analysis. The principal component of each category is reported in Table 1 and used as additional dependent variable.

Adoption of any of the practices listed in Table 1 is potentially subject to strategic complementarities, although these complementarities may involve economic agents other than the manufacturing firms on which we focus. With this caveat in mind, we begin by reporting variables related to technology broadly defined. The first variable is the answer to a question that asked whether the firm introduced a new product or technology in the year preceding the survey. Between a third and a half of surveyed firms responded positively to this question, implying that the rest, i.e., the majority of surveyed firms did not. A non-negligible proportion of surveyed

[2] ISO certification is an internationally recognized third-party guarantee of quality based on external validation of a firm's internal procedures for quality control.

[3] This is not true for many microenterprises but microenterprises are not included in the analysis since both ICA surveys condition participation in the survey on respondent firms having a minimum number of paid employees.

firms state having an R&D department, but the overwhelming majority does not. We also note some usage of IT technology, mostly in the form of email. At the time of the surveys, few manufacturing firms in Sudan or Ethiopia had a website.

The development of new products and the adoption of a new production technology potentially generate strategic complementarities across firms: if other firms innovate, remaining competitive may require that the firm innovate as well in order to remain competitive. But the incentive to innovate nevertheless exists even when other firms do not innovate. Thus, although diffusion may be reinforced by strategic complementarities, if the profitability of a product or technology has been demonstrated by another firm, copying the same product or technology generates individual benefits that are not subject to coordination failure.

Information on internal governance and investment in human capital is presented next. We first report the ratio of non-production to production workers. Non-production workers include professionals, managers, administrators, and sales personnel. Fafchamps and Söderbom (2006) argue that this ratio is related to the ease with which firms manage their labor force, and they show that many African firms are top-heavy, with a high ratio of production-to-non-production workers in spite of the relative simplicity of their production processes. Here we find a higher ratio in Sudan than in Ethiopia, consistent with firms' lower capacity to manage their workforce with a small number of clerks and managers. Labor management can be facilitated if workers are better trained. Surveyed firms were asked whether they had provided any in-house training to their workers, or sent any of them to a formal training course in the year preceding the survey. In both countries a substantial minority of firms did provide training to their workers, but the majority did not.

Workers trained by one firm may be hired by other firms, making worker training a strategic substitute: if other firms offer vocational training, my firms need not do it if I can hire their trained workers. This may hinder diffusion of the practice, or generate negative correlation across firms in the same sector, as some firms free-ride on others. For hierarchical management, strategic complementarities may arise through the operation of the labor market. If workers are unused to working in a hierarchical environment, the firm may need to hire more middle management and clerical workers in information processing, monitoring, and coordination tasks. Hence a firm that first institutes a multi-tiered structure may benefit others through the learning effect it has on the workforce. These effects, however, are likely to extend beyond the manufacturing sector which, in the two study countries, accounts for a small proportion of total employment. Still, we may observe some similarities among firms that are close in a network sense.

The next panel of Table 1 covers contractual practices. Firms were asked whether they import inputs directly from abroad. The alternative is to source inputs locally or to purchase inputs from an importer. Buying directly from abroad requires trust but is likely to improve the adequacy of the raw materials to the firm's production process. We find some difference between the two countries, with landlocked Ethiopia lagging behind Sudan. Firms were also asked whether they sell on credit to any of their customers. The main alternative is payment on delivery. A majority of manufacturing firms sell on credit to at least some of their customers, but a large minority do not. The data also show that sub-contracting part of production to other firms is rare.

Importing directly from suppliers abroad – as opposed to buying from a local importer – requires a modicum of trust that ultimately relies on a good market environment – e.g., predictability of the handling and custom operations at the port of entry. Presumably, the more firms import directly, the more knowledge they collectively acquire regarding procedures and sources of supply, and the more this information can diffuse among firms. There is therefore room for diffusion of practices through the diffusion of information along business networks.

Supplier credit is closely associated with invoicing, and was used in the conceptual section as example of strategic complementarities across firms: the more likely other suppliers are to offer supplier credit to clients, the less perilous it is to offer supplier credit as well. According to this reasoning, we expect supplier credit to diffuse more easily among suppliers who have the same clients – or clients in the same geographical area.

Next we examine the extent to which surveyed firms rely on reputation to enforce contracts with suppliers and clients. Respondents were asked five closely related questions as follows:

1. If you have a dispute with a customer, will other customers find out?
2. If some other firm has a dispute with customer, will you refuse to deal with the customer?
3. If you have a dispute with a customer, will other firms refuse to deal with the customer?
4. If you have a dispute with a supplier, will other suppliers find out?
5. If you have a dispute with a supplier, will other firms refuse to deal with the supplier?

For each of these questions we code $y = 2$ for yes, $y = 1$ for maybe / don't know, and $y = 0$ for no, hence high values correspond to stronger reputation effects. The summary statistics presented in Tables 1 and 2 suggest that news about a dispute often travel to customers and suppliers. They also suggest that the reputational sanction imposed on customers and suppliers involved in a dispute is not severe: firms typically continue to deal with customers and suppliers that have been involved in a dispute. These findings suggest that reputation mechanisms are weak, a point already made by Bigsten et al. (2000) and by Fafchamps (2004) for African manufacturing.

Firm performance indicators are reported at the bottom of Table 1. The first variable in the list is (the log of) value added per employee, expressed in US$, which is a crude indicator of productivity.[4] The country averages for this variable correspond to USD 1,700 for Ethiopia and USD 5,900 for Sudan. We also report available information about reported growth in employment and revenue.[5] Surveyed firms often report considerable growth in employment and revenue, although there is massive variation across firms and between years, as suggested by the comparison between the one-year growth and the three-year growth in revenues.

A key module of the survey contains information about the names of the firms' trading partners and their approximate geographical location. Respondents were asked to name up to three clients and three suppliers. They were also asked to provide the geographical location where each of the listed clients and suppliers is based. Using the information from this module, we construct simple measures of network proximity between firms in the two samples. These measures are reported in Table 2.

We begin by constructing a dyadic dataset of unique firm pairs. For instance, there are 304 firms in the Ethiopian sample. This means that there exist $304 \times 303/2 = 46,056$ unique enterprise pairs (i, j) in that sample. For each i, j pairs, we construct dummy variables capturing different concepts of network proximity. When two firms are close in the sense of that network, we say they are linked. The most direct network proximity measure we use is whether i and j buy or sell from each other. We are only able to identify a small number of such links in our data – 60 in Ethiopia and 5 in Sudan. That there are so few upstream and downstream links among sample firms is partly driven by the focus of the surveys on light manufacturing sector for which clients seldom are manufacturers.

We also construct dummy variables indicating whether i and j have a common supplier or

[4] Surveyed firms were asked to estimate the replacement value of their equipment and machinery, but much of this information is either missing or unreliable. This is hardly surprising given how thin the secondary market for equipment is in both countries. It is therefore very difficult for respondents to estimate how much it would cost to replace their – often antiquated – equipment.

[5] Reported as the $\log(X_t/X_{t-1})$ where X is employment or revenue, respectively. If the growth g rate of X is small, then $\log(X_t/X_{t-1}) \approx g$.

a common client. These types of links are more common: there are 481 (171) supplier-based links and 273 (678) client-based links in the Ethiopian (Sudanese) data, respectively. The next proximity dummy is whether i and j belong to the same manufacturing sector. The last one is geographical distance, already discussed earlier in this Section. These five proximity variables constitute our $\mathbf{g}_{ij}$ vector.

4. Empirical Analysis

As explained in conceptual section, our objective is to test whether the indicators of innovation adoption listed in Table 1 are more similar among firms that are close according to the network proximity variables listed in Table 2. To recall, the model we estimate is of the form:

$$|y_i - y_j| = \mathbf{g}_{ij}\boldsymbol{\theta}+\omega d_{ij}+|\mathbf{z_i} - \mathbf{z_j}|\boldsymbol{\gamma}+u_{ij} \tag{4.1}$$

A large value of the dependent variable means that firms i and j are dissimilar in terms of y.[6] The vector $\mathbf{g}_{ij}$ includes dummy variables for whether firms i and j buy from, or sell to, each other, have a common supplier, and a common client. The null hypothesis is that differences in the rate of diffusion cannot be attributed to network status. This would be the case if technology or contractual practices, for example, spread equally fast (or slowly) within and between networks. In contrast, if diffusion is more rapid within than between networks, $E[|y_i - y_j|]$ should be lower across linked than non-linked firms. In this case, we would obtain a negative coefficient on the relevant network indicator(s) in the vector $\mathbf{g}_{ij}$. For geographical distance d_{ij}, defined as the log of the distance between i and j plus one, the interpretation of the sign of ω is the opposite. Note

[6] When y is continuous, similarly in practices could alternatively be captured by expressing the dependent variable as $(y_i - y_j)^2$. Just like a least absolute deviation regression is thought to be more robust to outliers than least squares, we expect results based on $|y_i - y_j|$ to be more robust than those based on $(y_i - y_j)^2$ because the latter gives more weight to unusually large values of y. We have nevertheless estimated models of the latter form for continous y's. Results, not shown here to save space, are similar to those with absolute differences.

that the results from our analysis will be uninformative about the absolute speed of diffusion. What they do shed some light on is whether there are systematic differences depending on network status.

The set of control variables $\mathbf{z}$ are those reported in the top panel of Table 1; they include a dummy equal to 1 if i and j belong to the same sector, and absolute differences across i and j in firm age, education of the manager, experience of the manager, gender of the owner, and firm size proxied by the log of the number of employees. A positive coefficient on $|z_i - z_j|$ thus implies that the outcome variable y is more similar for firms that have a similar variable z. We estimate the model (4.1) using linear regression (OLS). Standard errors are bootstrapped so as to be robust to heteroskedasticity and dyadic correlation in the error terms across enterprises.[7]

4.1. Technology

We begin by investigating the association between network proximity and technology acquisition and usage. We construct dyadic dependent variables using data on whether firms have introduced a new product or technology in the year preceding the survey; whether the firms do any R&D; and the extent of IT usage.[8] Results are shown in Table 3, columns [1]-[3] for Ethiopia and columns [5]-[7] for Sudan. In columns [4] and [8] we report similar results using the principal component of all three categories as dependent variable.

In both countries, estimated coefficients of the same sector dummy are negative throughout, and significant in a number of individual regressions and for principal components. This indicates that firms in the same sector tend to have similar practices in terms of technology acquisition and usage.

[7] The reason we use bootstrapping instead of the approach suggested by Fafchamps and Gubert (2007) is that their formula, based on that of Conley (1999), is not guaranteed to generate positive variances, and this raises problems in our data.

[8] Recall we distinguish three levels of IT usage in the data, thus the underlying variable is set to 0 if IT is not used at all; 1 if the firm uses e-mail; and 2 if the enterprise has a business website.

The estimated effects of network proximity differ quite a bit across the two countries. For Ethiopia, the coefficients on the dummies for whether i and j trade with each other, have a common supplier, and a common client are small and statistically insignificant throughout. For Sudan, however, we find strong negative effects of trade and having a common supplier on the absolute dyadic difference in the R&D variable. That is, Sudanese firms that trade with each other, or have a common supplier, tend to record a more similar behavior with respect to R&D than other firms. These effects are statistically significant at the 1% level. Firms in Sudan that have a common supplier also tend to differ less than other firms with respect to IT usage. Not surprisingly, the coefficient of the same supplier dummy is also negative and statistically significant in the principal component regression.

We further find that Sudanese firms with a common client tend to differ *more* than other firms with respect to R&D and IT usage. This could be because clients concentrate purchases of a certain type of product to a single firm. For example, suppose a client demands sophisticated products and simple products. Suppose the client buys all the sophisticated products from a firm that specializes in the production of such goods (which requires R&D) and all the simple products from a different firm that specializes in simple goods (which does not require R&D). In such a case, firms that share the same client fill different, rather than similar, client needs. This would give rise to the empirical result observed here.

Now consider the role of geographical distance between firms. As discussed in Section 2, quite different mechanisms may be at play. On the one hand, geographical distance may be a serious obstacle to technology diffusion. On the other hand, adoption decisions may be local strategic substitutes. The regression results suggest that strategic substitution effects dominate strategic complementarities normally associated with technology diffusion. For Ethiopia, the distance coefficient is negative and statistically significant at the 10% level or better in all three models.

That is, closer geographical proximity tends to be associated with greater differences, with respect to technology acquisition. This is consistent with the 'supermarket' model discussed in Section 2. For Sudan the results are similar: the distance coefficient is negative and statistically significant in the models for R&D and IT usage, and for the principal component. Dyadic differences in the introduction of a new technology or product, however, appear not to be related to geographical distance for Sudan, perhaps because the effects of diffusion and strategic substitution cancel each other out in this case.

The control variables in these regressions have some explanatory power. The coefficient on the dummy for whether i and j belong to the same sector is negative and significant in three of the specifications, suggesting that technology acquisition tends to be more similar across firms in to the same sector than across firms in different sectors. The coefficient on firm size is positive in all specifications and statistically significant in five of the models considered. This implies that firms of similar size tend to record similar patterns of technology upgrading. The coefficient on gender difference is positive and significant in three of the specifications, suggesting that individuals of the same sex select similar technology. For the remaining control variables, the results are weaker and more mixed. Differences in managers' experience do not seem to matter except for IT usage in Ethiopia where we find a positive and significant coefficient. Firm age has insignificant coefficients across all specifications except in column (6) where the effect is negative and significant. The coefficients on managers' experience are insignificant throughout.

4.2. Human capital and internal governance

Table 4 shows regression results for models of human capital and internal governance of firms. Our measure of internal governance, namely the ratio of non-production workers to total employment, is only weakly related to the explanatory variables: in both Ethiopia and Sudan we cannot reject the hypothesis that all slope coefficients are jointly equal to zero. Internal governance, at least to the extent we can measure it, seems to be idiosyncratic to individual firms.

For in-house and external training, in contrast, we find some evidence of similarity across firms in the same industry: the 'same sector' dummy is significant for one of the training regressions in both Ethiopia and Sudan. The coefficients on direct link and same supplier dummies, however, are never significant.

We also find some evidence of substitution effects. The coefficient on distance is negative and statistically significant in both training regressions for Ethiopia and in the in-house training regression in Sudan. This implies that, other things being equal, firms located close to each other tend to differ *more* with respect their skills upgrading decisions than firms located far apart. We also find that the coefficient of the common client dummy is positive and is significantly different from zero in two cases. This means that firms with a common client have more different training policies than if they do not share a common client.

Why this is the case is not entirely clear. One possibility, often emphasized in the literature on agglomeration effects (e.g., Henderson 1988; Glaser et al. 1992), is that firms hire workers trained by other firms: the more other firms nearby provide the necessary training, the less they need to do so themselves. If firms that sell to the same clients produce close substitutes, they probably have similar production technology and similar manpower needs and can thus free ride on the training offered by other firms. Training decisions thus appear to be strategic substitutes.

With respect to other coefficients, we find that, as could be expected, firms of similar size tend to adopt more similar training decisions than firms of differing size. This probably reflects underlying differences in the need for skills across firms of differing size. We also note that the coefficients on the other control variables are mostly insignificant; where they are significant, the coefficients are negative, which further supports the notion that similarities in characteristics sometimes imply differences in decisions.

4.3. Contractual practices

Next we investigate whether contractual practices correlate across firms. We focus on three measures of contractual practices: whether the firm imports inputs directly; whether it sells on credit; and whether it sub-contracts part of its production. Results are shown in Table 5.

For Sudan we find a significantly negative coefficient on the direct link dummy on direct imports, selling on credit, and for the principal component regression: firms that buy and sell from each other tend to have more similar contractual practices. Sudanese firms that have a common supplier also tend to differ less than other firms with respect to direct imports, although this effect is only statistically significant at the 10% level. For Ethiopia, in contrast, the correlation between network proximity and similarity in contractual practices is weak and largely inconclusive.

Distance coefficients vary a lot across regressions. In two regressions they are positive and significantly different from zero (direct import and selling on credit in Sudan), suggesting that firms located close by have more similar contractual practices. But in two other regressions the coefficients are significantly negative (direct import in Ethiopia and subcontracting in Sudan). In both countries distance is not significant in the principal component regressions. It is thus hard to see a pattern here, perhaps because the relative importance of strategic substitution and diffusion varies from one contractual practice to another.

4.4. Reputation mechanisms

We now examine whether there is any evidence in our data that network links facilitate the diffusion of information on contractual disputes between suppliers and clients. To this effect, we rely on the data on the perceived consequences of disputes discussed in Section 3. Coding $y_i = 2$

for yes, $y_i = 1$ for maybe / don't know, and $y_i = 0$ for no, we compute $|y_i - y_j|$ for every pair of firms in the data and use this as dependent variable. The theoretical literature has emphasized the role that diffusion of information on contractual disputes along social networks plays in the development of modern market institutions (e.g., North 1990, Greif 1993). Consequently we expect to find a strong correlation in answers along social networks.

Regression results, shown in Table 6, do not confirm to theoretical expectations. Except in a couple of isolated cases where a social network regressor is significant – but with opposite signs – social network variables are not significant. One possible explanation could be insufficient power: each of the five perceived consequence variable may contain insufficient information to identify social network coefficients. Does combining the information from the five variables lead to better results? Not really: only one social network variable is significant in the principal component regression for Ethiopia, and none for Sudan. The coefficients on the control variables are also insignificant in the vast majority of cases, indicating that responses to question on perceived consequences of disputes are too idiosyncratic to uncover systematic relationships.

As pointed out Section 2, there are two possible interpretations to these findings: either information about contractual disputes does not diffuse along the kind of social networks we have able to measure; or information diffuse so well that social links do not matter. One way to identify which of these two interpretation is more likely is to examine the coefficient of the distance variable: even though information may diffuse rapidly along social networks within certain areas, information diffusion need not happen everywhere. This is because strategic complementarities in diffusion create the possibility of multiple equilibria. If this is the case, we expect to find that firms located far away from each other perceive the consequences of contractual disputes differently.

This is not what we find. For Ethiopia, the distance coefficient is negative and highly significant in three of the specifications but positive and weakly significant in the remaining two. The principal component of the five individual variables is negatively and significantly related to distance. For Sudan, the distance coefficient is negative and significant in two out of five individual regressions, and in the remaining cases it is not statistically significant. These findings are difficult to reconcile with the idea of widespread diffusion of contractual information among firms in the same location. If multiple equilibria are present, they seem to coexist within locations, so that some firms recognize there are reputational consequences to contractual disputes, while others in the same location do not.

4.5. Firm performance and growth

So far we have focused on technology decisions and business practices that may diffuse along social networks. In this sub-section we focus on firm performance directly: ultimately we care about the adoption of technological and institutional innovations because we believe that they improve firm productivity and performance. While we have found social network effects to be rather weak, some of our empirical results are consistent with strategic substitution. We now investigate whether these results are mirrored in labor productivity and growth rates. These are crude indicators of firm performance, but they are easier to measure than total factor productivity which we do not have sufficient data to estimate for each firm.

In modeling these outcomes, the dependent variable is defined as before as the absolute difference between to the two firms performance indicators. Results are shown in Table 7. In Ethiopia we find little evidence that firms that are closer in the social network sense have more similar performances: the same supplier dummy is the only statistically significant network variable, but has the wrong sign. The situation is not improved by combining the available performance information into a single principal component variable. In Sudan, we find that firms that share the same supplier have consistently more similar performances than firms that do not. We also find a significantly negative coefficient for the direct link dummy in the employment regression, and a significant coefficient for the same client dummy in the employment growth regression. As in earlier Tables, we find limited evidence that there is more dissimilarity among firms located nearby: distance has a significantly negative coefficient in two of the regressions – but it is significantly positive in another. The overall conclusion from Table 7 is that network links and geographical proximity are not associated with convergence in performance across firms.

4.6. Robustness

We conducted a large number of robustness checks. Firstly, for continuous variables y_i we repeated the analysis using covariance in outcomes rather than the absolute difference as dependent variable. We thus compute $(y_i - \bar{y})(y_j - \bar{y})$ for every pair of firms in our data and use this as dependent variable. Note that this affects the interpretation of the signs of the estimated coefficients. If diffusion is stronger within than between networks, for example, we expect $E[(y_i - \bar{y})(y_j - \bar{y})]$ to be *higher* across linked than non-linked firms and thus the coefficient on the relevant network indicator(s) in the vector $\mathbf{g}_{ij}$ should be *positive*. Keeping this caveat in mind, results are fairly similar to those reported here in the sense that they fail to provide strong evidence of network effects in Ethiopia.

To investigate whether strategic substitution primarily operations within sectors, we add an interaction term between distance and the same sector dummy. If strategic substitution is stronger within sectors, the interaction term should be negative. There's no support for this idea in the data. Only in 2 cases out of a total of 46 regressions do we get a significant coefficient on the interaction term, and in both cases the coefficient is positive rather than negative.

The results thus suggest that, within local markets, firms tend to be different from each other regardless of sector. Why strategic substitution effects operate across sectors is unclear. It could be due, for example, to the fact that few consumers can afford to buy expensive high-tech products. In this case, if there's a high-tech textile firm in an area, it may not be a good idea to set up a high-tech metal firm in the same area because there is limited purchasing power for high-tech consumer products; it is better for a new entrant to produce low-tech metal products. Similar examples could be constructed for the decision to train workers or to offer credit to customers.

5. Conclusions

In this paper we have documented empirical patterns of correlation in the adoption of technological innovation and contractual practices among manufacturing firms in Ethiopia and Sudan. Our empirical analysis is based on network data indicating whether any two firms in our sample do business with each other, whether they buy inputs from a common supplier, and whether they sell output to a common client.

Our results provide limited support for the commonly held idea that firms that are more proximate in a network sense are more likely to adopt similar contractual and technological innovation practices. In this respect the strongest results are for technology and for firm performance, but for the latter only in Sudan.

We also find some evidence that, for certain practices, adoption decisions are local strategic substitutes, so that if one firms adopts, others nearby are less likely to do so. We note that, in several ways, the empirical results are out of tune with the present policy discussion of how the economic performance of African's manufacturing sector can be improved.

References

[1] Bigsten, Arne, Paul Collier, Stefan Dercon, Marcel Fafchamps, Bernard Gauthier, Jan Willem Gunning, Abena Oduro, Remco Oostendorp, Catherine Pattillo, Måns Söderbom, Francis Teal, and Albert Zeufack (2000). "Contract Flexibility and Dispute Resolution in African Manufacturing," *Journal of Development Studies* 36:4, pp. 1-37.

[2] Casella, Alessandra and James Rauch (2002), "Anonymous Market and Group Ties in International Trade", *Journal of International Economics*, 58(1): 19-47, October 2002

[3] Conley, T.G. 1999. "GMM Estimation with Cross-Sectional Dependence." *Journal of Econometrics* 92(1):1–45.

[4] de Mel, Suresh, David McKenzie and Christopher Woodruff, (2009). "Are Women More Credit Constrained? Experimental Evidence on Gender and Microenterprise Returns," *American Economic Journal: Applied Economics*, 1(3): 1-32, July

[5] Doshi, Gaurav (2011). "Overview of Bangladesh Garment Industry", available at http://ezinearticles.com/?Overview-of-Bangladesh-Garment-Industry&id=367773

[6] Fafchamps, Marcel and Bart Minten (2001). "Property Rights in a Flea Market Economy", *Economic Development and Cultural Change*, 49(2): 229-268, January 2001

[7] Fafchamps, Marcel (2004). *Market Institutions in Sub-Saharan Africa: Theory and Evidence*, MIT Press, Cambridge, Mass.

[8] Fafchamps, Marcel (2010). "Spontaneous Markets, Networks, and Social Capital: Lessons from Africa", in *Institutional Microeconomics of Development*, Timothy Besley and Rajshri Jayaraman (eds.), CESifo Seminar Series, MIT Press, Cambridge Mass.

[9] Fafchamps, Marcel (2003), "Ethnicity and Networks in African Trade", *Contributions to Economic Analysis and Policy*, Berkeley Electronic Press at www.bepress.com, 2(1): article 14

[10] Fafchamps, Marcel and Måns Söderbom (2006). "Wages and Labor Management in African Manufacturing", *Journal of Human Resources*, 41(2): 346-79, Spring 2006

[11] Fafchamps, M. and F. Gubert. 2007. "The Formation of Risk Sharing Networks", *Journal of Development Economics*, 83(2), 326-50.

[12] Fafchamps, Marcel, Said El Hamine and Albert Zeufack (2008). "Learning to Export: Evidence from Moroccan Manufacturing". *Journal of African Economies*, 17(2): 305-55, March 2008

[13] Glaeser, Edward L., Hedi D. Kallal, Jose A. Sheinkman, and Andrei Shleifer (1992). "Growth in Cities", *J. Polit. Econ.*, 100(6): 1126-1152, December 1992

[14] Greif, Avner (1993). "Contract Enforceability and Economic Institutions in Early Trade: The Maghribi Traders' Coalition", *Amer. Econ. Rev.*, 83(3): 525-548, June 1993

[15] Griliches, Ziv and F. Lichtenberger (1984). "Intraindustry Technological Flows and Productivity Growth: A Reexamination", *Review of Economics and Statistics*, LXVI(2)

[16] H&H Consultancy. 2008. *Sudan Investment Climate Survey I: Final Survey Report*, April 2008. Report submitted to the World Bank.

[17] Helmers, Christian (2010). "Choose the Neighbor Before the House: Agglomeration Externalities in UK Science Parks", Department of Economics, Oxford University (mimeograph)

[18] Henderson, J. Vernon (1988). *Urban Development: Theory, Fact, and Illusion*, Oxford University Press, New York

[19] Jackson, Matthew O. (2009). *Social and Economic Networks*, Princeton University Press, Princeton

[20] Kraay, Aart & Soloaga, Isidro & Tybout, James, (2002). "Product quality, productive efficiency, and international technology diffusion : evidence from plant-level panel data," *Policy Research Working Paper Series* 2759, The World Bank

[21] Mengistae, T. and Honorati, M. 2009. "Constraints to productivity growth and to job creation in the private sector". Chapter 2 in *Ethiopia Investment Climate Assessment*. Washington DC, World Bank.

[22] North, Douglas C. (1990). *Institutions, Institutional Change, and Economic Performance.* Cambridge University Press, Cambridge

[23] Parente, Stephen L & Prescott, Edward C, (1994). "Barriers to Technology Adoption and Development," *Journal of Political Economy*, University of Chicago Press, vol. 102(2), pages 298-321, April

[24] Rauch, James E. and Alessandra Casella (2003), "Overcoming Informational Barriers to International Resource Allocation: Prices and Ties", *Economic Journal*, 113(484): 21-42, January 2003

[25] Sonobe, Tetsushi and Keijiro Otsuka (2011). *Cluster-Based Industrial Development: A Comparative Study of Asia and Africa*, Palgrave McMillan, London

[26] Sutton, John (1998). *Technology and Market Structure: Theory and History*, MIT Press, Cambridge and London

[27] Tybout, James R. (2000), "Manufacturing Firms in Developing Countries: How Well Do They Do and Why?", *Journal of Economic Literature*, 38(1): 11-44, March 2000

[28] Vega-Redondo, Fernando (2006). *Complex Social Networks*, Cambridge University Press, Cambridge

[29] Young, H. Peyton and Mary A. Burke (2001). "Competition and Custom in Economic Contracts: A Case Study of Illinois Agriculture", *American Economic Review*, 91(3): 559-73, June 2001

Table 1. Summary Statistics

	Ethiopia				Sudan				
1. Firm characteristics	n.obs.	mean	std.dev.	loadings	n.obs.	mean	std.dev.	loadings	Description of variable
Firm age	304	17.93	16.14		401	15.21	14.1		Years
Education of top manager	303	2.71	1.2		399	2.92	1.25		see note (a)
Experience of top manager	304	14.5	9.77		395	17.2	12.93		Years
Any female owner?	304	23.0%			382	15.2%			0=no; 1=yes
Log(firm employment)	304	3.37	1.66		399	2.61	1.14		
2. Technology									
Did you introduce a new product or new technology last year?	304	34.9%		0.79	391	47.8%		0.66	0 = no, 1 = yes
Does the firm do any research and development?	304	13.2%		0.80	388	22.9%		0.82	0 = no, 1 = yes
IT usage	304	0.586	0.762	0.44	401	0.454	0.780	0.71	0 = nothing, 1=email, 2=website
3. Human capital and internal governance									
Ratio of non-production workers to total employment	304	27.2%	0.169	0.24	398	42.2%	0.296	0.22	Percentage; see note (b)
Any in-house training of staff last year?	304	28.0%		0.83	397	26.7%		0.80	0 = no, 1 = yes
Staff sent to formal training course last year?	304	28.0%		0.84	398	12.3%		0.80	0 = no, 1 = yes
4. Contractual practices									
Any direct imports of inputs?	304	30.6%		0.67	401	50.9%		0.74	0 = no, 1 = yes
Do you sell on credit?	304	53.3%		0.65	401	64.3%		0.73	0 = no, 1 = yes
Does firm sub-contract production?	302	11.6%		0.33	382	9.4%		0.22	0 = no, 1 = yes
5. Reputation mechanism									
If you have a dispute with a customer, will other customers find out?	304	1.049	0.948	0.47	400	0.808	0.934	0.48	0 = no, 1 = maybe, 2 = yes
If another firm has a dispute with a customer, will you refuse to deal with that customer?	304	0.457	0.815	0.67	401	0.783	0.954	0.65	0 = no, 1 = maybe, 2 = yes
If you have a dispute with a dispute, will other firms refuse to deal with that customer?	304	0.474	0.717	0.43	401	0.788	0.899	0.63	0 = no, 1 = maybe, 2 = yes
If you have a dispute with a supplier, will other suppliers find out?	304	0.914	0.926	0.46	401	0.783	0.925	0.69	0 = no, 1 = maybe, 2 = yes
If you have a dispute with a supplier, will other firms refuse to deal with that supplier?	304	0.398	0.682	0.47	401	0.656	0.861	0.64	0 = no, 1 = maybe, 2 = yes
6. Firm performance and growth									
Log(value-added per employee)	284	7.44	1.268	0.20	203	8.680	3.177	0.45	Log USD
Employment growth last 3 years	282	0.225	0.605	0.38	346	0.040	0.784	0.40	Dlog
Revenue growth last year	287	0.251	0.66	0.80	301	0.424	1.598	0.67	Dlog
Revenue growth last 3 years	270	0.493	1.265	0.81	259	-0.471	2.212	0.80	Dlog

Notes: (a) 1=less than secondary, 2=secondary, 3=vocational, 4=university. (b) Non-production workers include professionals, managers, administrators, sales personnel.

Table 2. Dyadic Data

	Number of pairs	
	Ethiopia	**Sudan**
Number of unique enterprise pairs	46,056	80,200
i & j trade with each other	60	5
i & j have a common supplier	481	171
i & j have a common client	273	678
i & j are in the same sector	13,033	9,490

Table 3. Correlates of Dyadic Differences: Technology Acquisition

	Ethiopia				Sudan			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Did you introduce a new product or new technology last year?	Does the firm do any research and development?	IT usage (0 = nothing, 1=email, 2=website)	First common factor	Did you introduce a new product or new technology last year?	Does the firm do any research and development?	IT usage (0 = nothing, 1=email, 2=website)	First common factor
	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$
i & j trade with each other	0.049	0.096	-0.070	0.175	0.015	-0.339	0.451	-0.387
	(0.389)	(0.887)	(0.374)	(0.772)	(0.038)	(8.049)**	(0.730)	(2.678)**
i & j have common supplier	-0.018	0.046	-0.063	0.008	-0.080	-0.183	-0.272	-0.341
	(0.438)	(1.131)	(0.955)	(0.100)	(1.080)	(2.828)**	(2.502)*	(2.472)*
i & j have common client	0.067	0.011	0.060	0.003	0.025	0.123	0.229	0.220
	(1.136)	(0.160)	(0.635)	(0.024)	(1.105)	(3.518)**	(3.773)**	(2.451)*
log Distance btw i & j	-0.005	-0.010	-0.017	-0.090	0.000	-0.012	-0.022	-0.030
	(2.008)*	(1.926)$^{+}$	(2.489)*	(2.538)*	(0.224)	(4.061)**	(4.158)**	(0.913)
i & j belong to same sector	-0.032	-0.022	-0.057	-0.020	0.005	-0.013	-0.096	-0.017
	(1.892)*	(1.542)	(2.023)*	(2.209)*	(0.455)	(0.720)	(3.166)**	(2.747)**
Abs diff firm age	-0.001	-0.001	-0.002	-0.003	0.000	0.000	-0.003	-0.001
	(1.067)	(0.953)	(1.429)	(1.560)	(0.427)	(0.349)	(2.654)**	(0.687)
Abs diff managers' education	0.009	-0.010	0.064	0.048	0.006	0.008	0.019	0.037
	(0.953)	(1.195)	(2.252)*	(1.891)$^{+}$	(0.920)	(0.816)	(1.132)	(1.804)$^{+}$
Abs diff managers' experience	-0.001	-0.001	-0.001	-0.004	0.000	0.000	0.000	0.000
	(0.851)	(0.439)	(0.584)	(1.878)	(0.018)	(0.355)	(0.013)	(0.163)
Owners' gender differ	-0.002	-0.006	0.090	0.024	0.001	0.098	0.435	0.250
	(0.079)	(0.196)	(1.991)*	(0.399)	(0.180)	(2.470)*	(4.784)**	(3.299)**
Abs diff log employment	0.006	0.030	0.190	0.107	0.023	0.039	0.167	0.177
	(0.661)	(2.214)*	(7.178)**	(3.112)*	(2.540)*	(2.255)*	(3.965)**	(3.816)**

Note: The table shows OLS results. A constant is included in all specifications. t-values are based on bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same individuals. Statistical significance at the 10%, 5% and 1% level is indicated by **, * and $^{+}$, respectively.

Table 4. Correlates of Dyadic Differences: Human Capital and Internal Governance

	Ethiopia				Sudan			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Ratio of non-production workers to total employment	Any in-house training of staff last year?	Staff sent to formal training course last year?	First common factor	Ratio of non-production workers to total employment	Any in-house training of staff last year?	Staff sent to formal training course last year?	First common factor
	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$
i & j trade with each other	-0.022	0.081	-0.045	-0.051	-0.086	-0.121	0.368	-0.200
	(0.654)	(0.754)	(0.339)	(0.234)	(0.911)	(0.422)	(1.034)	(0.562)
i & j have common supplier	0.014	0.044	0.011	0.086	0.000	0.031	-0.020	0.074
	(0.964)	(0.928)	(0.275)	(1.072)	(0.008)	(0.372)	(0.355)	(0.507)
i & j have common client	0.016	0.040	0.127	0.215	-0.040	0.083	0.021	0.174
	(0.681)	(0.533)	(2.026)**	$(1.738)^+$	(1.396)	(2.202)*	(0.294)	(1.229)
log Distance btw i & j	-0.002	-0.017	-0.015	-0.048	0.002	-0.008	0.000	-0.064
	(0.498)	(5.613)**	(5.260)**	$(1.833)^+$	(0.340)	(2.547)*	(0.091)	$(1.721)^+$
i & j belong to same sector	-0.002	-0.017	-0.030	-0.025	0.003	-0.034	-0.009	-0.006
	(1.216)	(1.409)	$(1.715)^+$	(3.045**)	(1.638)	(1.805)	(0.546)	(0.722)
Abs diff firm age	0.000	0.000	0.002	0.002	-0.001	0.000	0.001	0.000
	(0.444)	(0.288)	(1.583)	(1.072)	$(1.745)^+$	(0.639)	(0.889)	(0.115)
Abs diff managers' education	-0.004	0.011	0.006	0.033	0.004	0.000	-0.015	-0.015
	(1.654)	(0.608)	(0.402)	(0.934)	(1.125)	(0.058)	(3.051)**	(1.130)
Abs diff managers' experience	0.000	-0.002	-0.001	-0.001	0.000	-0.002	0.001	-0.001
	(0.446)	(2.079)*	(1.153)	(0.506)	(0.432)	(3.095)**	(0.589)	(0.405)
Owners' gender differ	0.008	0.018	-0.012	-0.005	0.030	0.045	0.085)	0.204
	(0.689)	(0.702)	(0.676)	(0.134)	$(1.692)^+$	(1.191)	(1.564)	$(1.783)^+$
Abs diff log employment	0.011	0.088	0.099	0.230	0.018	0.057	0.078	0.207
	(2.246)*	(5.659)**	(6.916)**	(7.436)**	(3.207)**	(3.334)**	(3.804)**	$(4.149)^+$

Note: The table shows OLS results. A constant is included in all specifications. t-values are based on bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same individuals. Statistical significance at the 10%, 5% and 1% level is indicated by **, * and $^+$, respectively.

Table 5. Correlates of Dyadic Differences: Contractual Practices

	Ethiopia				Sudan			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Any direct imports of inputs?	Do you sell on credit?	Does firm sub-contract production?	First common factor	Any direct imports of inputs?	Do you sell on credit?	Does firm sub-contract production?	First common factor
	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$
i & j trade with each other	0.025	-0.012	0.110	0.114	-0.423	-0.436	0.049	-0.813
	(0.209)	(0.117)	(0.922)	(0.452)	(12.13)**	(12.61)**	(0.132)	(3.692)**
i & j have common supplier	-0.019	-0.001	0.076	-0.116	-0.145	0.015	0.048	0.030
	(0.371)	(0.032)	(2.065)*	(1.549)	$(1.901)^{+}$	(0.190)	(0.591)	(0.225)
i & j have common client	0.084	-0.014	0.077	0.184	-0.046	-0.008	-0.031	-0.039
	(1.465)	(0.265)	(1.090)	(1.481)	(1.084)	(0.177)	(0.476)	(0.391)
log Distance btw i & j	-0.012	0.000	0.005	-0.037	0.008	0.009	-0.009	-0.046
	(2.142)*	(0.178)	(0.791)	(1.288)	(2.591)*	(2.171)*	(2.078)*	(1.643)
i & j belong to same sector	-0.040	-0.017	-0.002	-0.009	-0.030	-0.006	-0.006	0.009
	(2.485)*	(1.107)	(0.212)	(1.138)	$(1.902)^{+}$	(0.440)	(0.435)	(0.926)
Abs diff firm age	0.000	0.001	-0.002	-0.004	0.000	0.000	-0.001	0.000
	(0.527)	(0.862)	(3.248)**	(2.882)**	(0.437)	(0.141)	(1.187)	(0.284)
Abs diff managers' education	0.030	0.001	-0.020	0.037	0.022	0.006	0.002	0.028
	(1.506)	(0.134)	(2.735)**	(1.335)	$(1.917)^{+}$	(0.888)	(0.344)	(1.609)
Abs diff managers' experience	-0.002	0.001	-0.002	0.005	0.000	0.000	0.000	-0.001
	$(1.948)^{+}$	(0.755)	(1.479)	(2.178)*	(0.321)	(0.292)	(0.627)	(0.523)
Owners' gender differ	0.046	0.004	0.024	0.040	0.003	-0.016	0.011	-0.002
	(1.541)	(0.412)	(0.768)	(0.957)	(0.380)	(1.309)	(0.286)	(0.054)
Abs diff log employment	0.132	0.003	0.015	0.138	0.066	0.005	-0.004	0.098
	(8.740)**	(0.547)	(1.138)	(4.437)**	(4.545)**	(0.633)	(0.323)	(3.694)**

Note: The table shows OLS results. A constant is included in all specifications. t-values are based on bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same individuals. Statistical significance at the 10%, 5% and 1% level is indicated by **, * and $^{+}$, respectively.

Table 6a. Correlates of Dyadic Differences: Perceived Consequences of Disputes

	Ethiopia					Sudan				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	If you have a customer dispute, will other customers find out?	If other firm has a customer dispute, will you refuse to deal with customer?	If you have a customer dispute, will other firms refuse to deal with customer?	If you have a supplier dispute, will other suppliers find out?	If you have supplier dispute, will other firms refuse to deal with supplier?	If you have a customer dispute, will other customers find out?	If other firm has a customer dispute, will you refuse to deal with customer?	If you have a customer dispute, will other firms refuse to deal with customer?	If you have a supplier dispute, will other suppliers find out?	If you have supplier dispute, will other firms refuse to deal with supplier?
	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$
i & j trade with each other	-0.187	0.033	-0.050	0.124	0.016	-0.704	-0.209	0.557	0.280	0.367
	(0.910)	(0.185)	(0.303)	(0.600)	(0.099)	(2.906)**	(0.305)	(1.131)	(0.409)	(0.519)
i & j have common supplier	-0.016	0.032	-0.061	-0.034	-0.049	-0.154	-0.083	-0.037	-0.105	-0.113
	(0.174)	(0.358)	(0.921)	(0.367)	(0.658)	(0.928)	(0.504)	(0.254)	(0.745)	(0.689)
i & j have common client	0.048	0.029	-0.059	0.008	0.085	0.058	0.033	-0.104	-0.105	0.112
	(0.604)	(0.227)	(0.594)	(0.082)	(0.768)	(1.039)	(0.491)	(0.900)	(0.946)	(2.362)*
log Distance btw i & j	0.011	-0.020	-0.017	0.010	-0.027	-0.007	-0.006	0.000	-0.003	-0.005
	(1.964)*	(3.422)**	(3.515)**	(1.918)$^{+}$	(5.063)**	(2.183)*	(1.972)*	(0.119)	(1.055)	(0.999)
i & j belong to same sector	-0.008	-0.016	0.002	-0.020	-0.011	-0.009	-0.021	-0.003	-0.001	0.028
	(0.306)	(0.630)	(0.089)	(0.793)	(0.610)	(0.408)	(0.755)	(0.155)	(0.069)	(1.682)$^{+}$
Abs diff firm age	0.000	-0.001	-0.002	0.001	0.000	-0.001	0.000	0.001	-0.001	0.002
	(0.447)	(0.418)	(1.516)	(0.819)	(0.039)	(1.202)	(0.362)	(0.562)	(0.855)	(0.986)
Abs diff managers' education	-0.004	-0.008	-0.009	-0.005	-0.008	0.001	0.003	0.002	-0.001	0.007
	(0.532)	(0.673)	(0.849)	(0.578)	(0.715)	(0.117)	(0.431)	(0.288)	(0.205)	(0.766)
Abs diff managers' experience	0.000	-0.001	0.003	0.001	0.003	0.001	0.000	-0.001	-0.001	-0.001
	(0.151)	(0.430)	(1.172)	(0.754)	(0.917)	(0.831)	(0.142)	(1.615)	(0.815)	(0.819)
Owners' gender differ	-0.008	-0.006	0.060	0.018	0.054	0.030	0.002	-0.010	0.016	0.026
	(0.599)	(0.109)	(1.091)	(0.615)	(0.905)	(0.888)	(0.056)	(0.410)	(0.405)	(0.566)
Abs diff log employment	0.002	-0.004	0.009	0.015	0.010	0.022	-0.013	-0.004	-0.027	-0.031
	(0.348)	(0.232)	(0.596)	(1.143)	(0.538)	(1.399)	(1.153)	(0.372)	(3.051)**	(2.347)**

Note: The table shows OLS results. A constant is included in all specifications. t-values are based on bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same individuals. Statistical significance at the 10%, 5% and 1% level is indicated by **, * and $^{+}$, respectively.

Table 6b. Correlates of Dyadic Differences: Perceived Consequences of Disputes, First Common Factor

	[1] Ethiopia	[2] Sudan
	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$
i & j trade with each other	0.146	0.338
	(0.706)	(0.390)
i & j have common supplier	-0.173	0.009
	(2.019)*	(0.062)
i & j have common client	0.106	0.057
	(0.573)	(0.651)
log Distance btw i & j	-0.047	0.016
	(1.242)	(0.827)
i & j belong to same sector	-0.029	0.007
	(3.042)**	(0.917)
Abs diff firm age	0.005	-0.001
	(1.248)	(1.203)
Abs diff managers' education	0.017	0.001
	(0.875)	(0.132)
Abs diff managers' experience	0.005	0.000
	(0.753)	(0.259)
Owners' gender differ	0.118	0.036
	(1.416)	(0.756)
Abs diff log employment	-0.010	-0.011
	(0.409)	(0.840)

Note: The table shows OLS results. A constant is included in all specifications. t-values are based on bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same individuals. Statistical significance at the 10%, 5% and 1% level is indicated by **, * and $^{+}$, respectively.

Table 7. Correlates of Dyadic Differences: Firm Performance and Growth

	Ethiopia					Sudan				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	Log(value-added per employee) $\lvert y_i - y_j \rvert$	Labor. growth last 3 years $\lvert y_i - y_j \rvert$	Revenue growth last year $\lvert y_i - y_j \rvert$	Revenue growth last 3 years $\lvert y_i - y_j \rvert$	First common factor $\lvert y_i - y_j \rvert$	Log(value-added per employee) $\lvert y_i - y_j \rvert$	Labor growth last 3 years $\lvert y_i - y_j \rvert$	Revenue growth last year $\lvert y_i - y_j \rvert$	Revenue growth last 3 years $\lvert y_i - y_j \rvert$	First common factor $\lvert y_i - y_j \rvert$
i & j trade with each other	-0.076	-0.085	-0.044	0.338	0.165		-0.534	-0.413	1.652	
	(0.267)	(0.655)	(0.360)	(0.515)	(0.390)		(5.545)**	(0.538)	(0.556)	
i & j have common supplier	-0.106	0.015	0.246	0.005	0.109	-1.651	-0.277	-0.904	-0.711	-0.481
	(0.960)	(0.228)	(2.171)*	(0.041)	(0.764)	(3.647)**	(2.262)*	(2.687)**	(2.030)*	(2.370)*
i & j have common client	-0.182	-0.014	0.195	-0.012	0.113	-0.986	0.090	-0.586	0.307	-0.009
	(1.336)	(0.147)	(1.290)	(0.059)	(0.578)	(1.495)	(0.648)	(2.878)**	(0.693)	(0.041)
log Distance btw i & j	-0.082	0.005	-0.004	-0.024	-0.013	-0.135	-0.056	-0.047	-0.062	-0.076
	(1.834)$^+$	(0.206)	(0.189)	(0.472)	(0.372)	(0.870)	(1.408)	(0.683)	(0.470)	(0.869)
i & j belong to same sector	-0.025	0.014	0.018	0.019	0.024	-0.061	-0.017	-0.052	-0.052	-0.010
	(2.029)*	(1.307)	(1.664)$^+$	(1.151)	(1.582)	(1.587)	(1.562)	(2.142)*	(1.491)	(0.552)
Abs diff firm age	-0.003	0.003	-0.003	-0.006	-0.004	-0.005	0.001	0.009	0.005	0.006
	(1.566)	(0.770)	(3.556)**	(3.498)**	(2.726)**	(0.631)	(0.516)	(1.325)	(0.615)	(1.311)
Abs diff managers' education	-0.007	0.004	-0.009	0.009	-0.016	0.046	-0.005	-0.033	-0.020	0.011
	(0.258)	(0.325)	(0.792)	(0.285)	(0.943)	(0.974)	(0.403)	(1.458)	(0.750)	(0.454)
Abs diff managers' experience	0.001	0.000	-0.003	-0.002	-0.004	-0.007	0.001	0.003	-0.004	-0.002
	(0.209)	(0.003)	(1.332)	(0.377)	(1.443)	(1.267)	(0.579)	(0.436)	(0.664)	(0.593)
Owners' gender differ	0.121	0.103	-0.081	-0.220	-0.110	0.375	-0.007	-0.161	0.056	-0.138
	(1.303)	(1.537)	(2.092)*	(3.205)**	(1.882)$^+$	(0.643)	(0.118)	(1.208)	(0.203)	(1.434)
Abs diff log employment	0.079	0.008	-0.026	-0.038	-0.024	0.007	0.065	0.091	0.102	0.061
	(2.526)*	(0.327)	(2.187)*	(1.042)	(1.057)	(0.065)	(2.532)*	(1.278)	(0.895)	(1.017)

Note: The table shows OLS results. A constant is included in all specifications. t-values are based on bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same individuals. Statistical significance at the 10%, 5% and 1% level is indicated by **, * and $^+$, respectively.

Figure 1. Diffusion of Invoicing

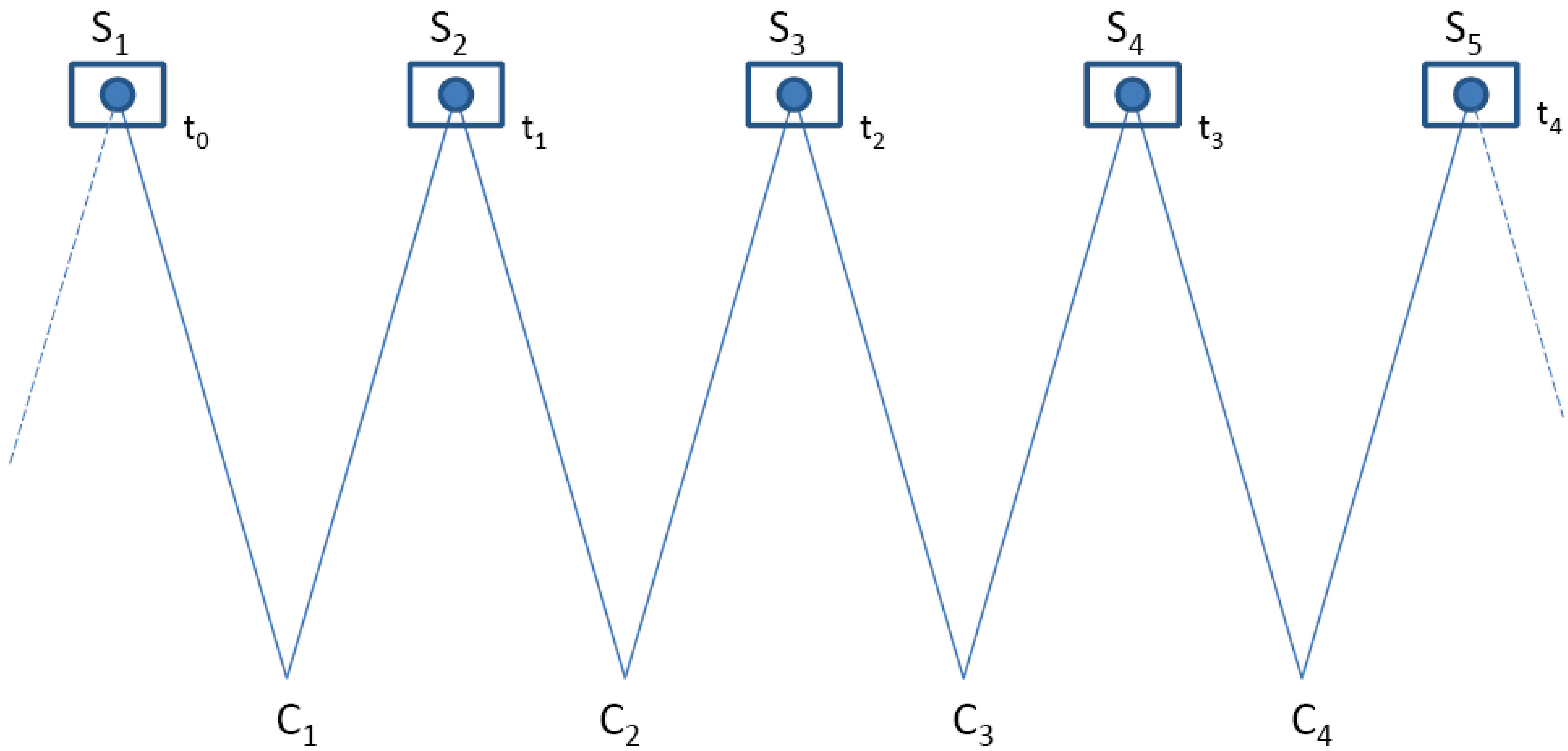

Figure 2. Survey locations in Ethiopia

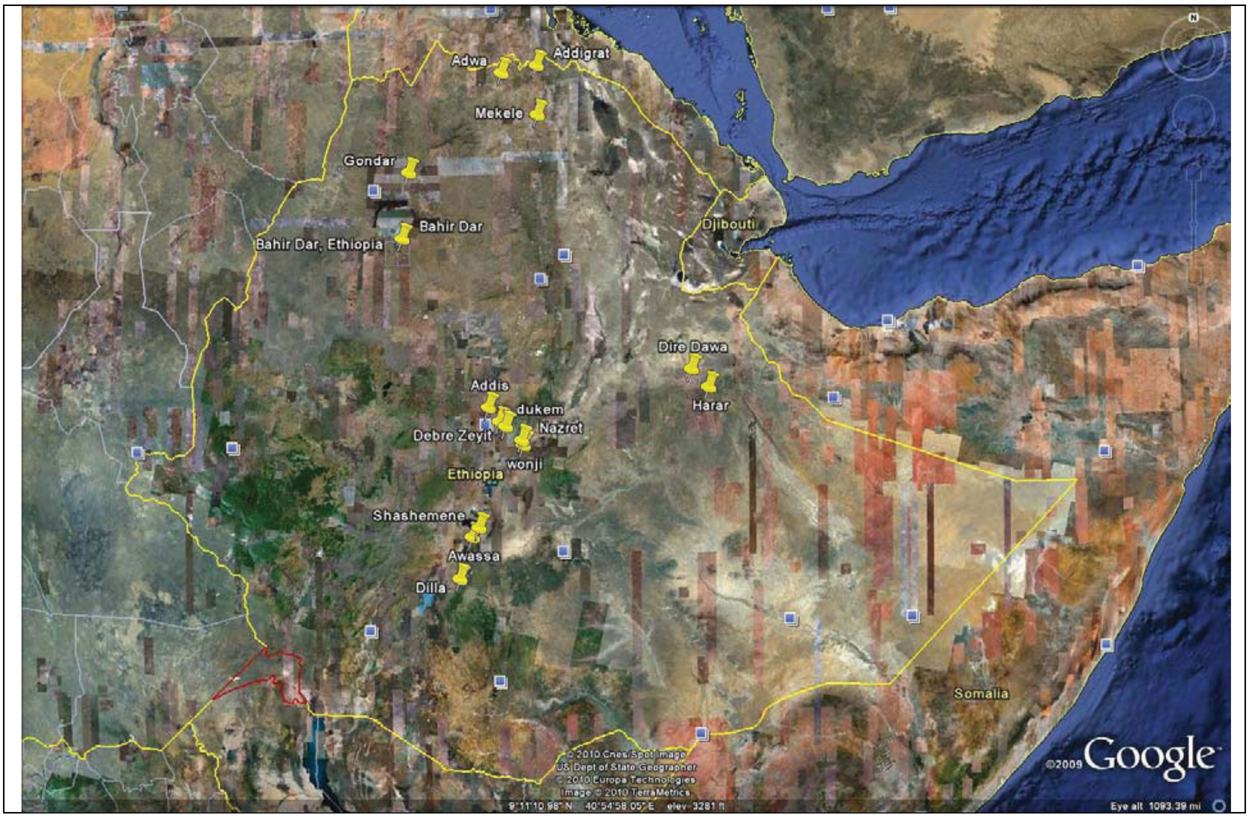

Figure 3. Survey locations in Sudan